Design of a Genetic-Algorithm-Based Steam Temperature Controller in Thermal Power Plants*

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Abstract—**This paper presents a systematic approach for the design of temperature controller using genetic algorithms (GAs) for thermal power plant subsystems and investigates the robustness of the designed control law. The proposed approach employs GA search for determination of the optimal PI controller parameters for a previously identified nonlinear de-superheater of a 4X 325 MW thermal power plant. Results indicate that the proposed algorithm significantly improves the performance of the thermal power plant sub-system.**

Keywords: Thermal power plants, Power plant control, Steam temperature control, Genetic algorithms, Neuro-fuzzy identification

1 INTRODUCTION

Power plant subsystems are generally nonlinear and the operating conditions may vary over a wide range subjected to various disturbances and noise. Control of superheater steam temperatures is one of the most widely discussed control problems in thermal power plants. The superheater process is part of the boiler process which itself is part of the thermal power plant. Most often boilers include superheaters at a number of levels. The boiler process includes several steam superheating processes which are divided into parallel heating surfaces, counting typically 4-8 high-pressure superheaters and 2-4 intermediate pressure superheaters. Each superheater process is equipped with an attemperator device (water injection at the inlet) for control of the steam outlet temperature of the superheater. The control problem is attractive from a theoretical point of view due to the complex characteristics of the superheater process:

- The dynamics is of high order (lumped system),
- The dynamics is load dependent,
- System is exposed to major disturbances.

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Due to these reasons, attaining tight control is remained a challenge for these industrial processes for years [1]-[3].

The thermal power plant under study has the capacity of 4X 325 MW, utilizes a superheating system, consisting of a primary and secondary de-superheater. Desupserheater outlet steam temperature control of this power plant is maintained by a ten-year-old PID controller. The performance of the de-superheater, with the existing system, does not show high quality set-point tracking ability. The main purpose of this work is to investigate the possibility of re-tuning of the operating controller or designing a more efficient control strategy to improve the performance of the system.

In this study an effective non-linear PI-like controller for the second left hand de-superheater operating in the steam power plant is designed using adaptive neuro-fuzzy inference system (ANFIS) [4] model of the process. A low order control scheme is developed based on PI controller design method and genetic algorithms in order to improve the performance of the existing control system.

2 BACKGROUND THEORY

2.1 Identification and Modeling

During the last 20 years, there have been significant developments in methods for model-based-control [5], [6]. Model-based control schemes require the existence of suitable process models. The least square error (LSE) method is proved to be the optimum algorithm for the modeling of linear systems [7], [8].

For nonlinear systems, lack of good nonlinear process models is a bottleneck for using model-based controllers. Among different approaches for modeling nonlinear systems, artificial neural networks (ANN), fuzzy logic (FL), and neuro-fuzzy systems (NFS) are widely used during the last ten years [9]-[11]. Having enough data for a long range of operating conditions, neuro-fuzzy networks are the most suitable structures for modeling nonlinear systems.

In this paper the most common structure of neuro-fuzzy networks, ANFIS [4], is considered. Figure 1 shows the scheme of a linear Sugeno type fuzzy inference system (FIS) [7]. In this structure, "antecedent" of rules contains fuzzy sets (as membership functions) and "consequent" is a first order polynomial (a crisp function). The structure shown in Figure 1(a) can be transformed to the neuro-fuzzy network shown in Figure 1(b). In this method, a fuzzy inference system is designed based on the system's specifications. This initial model is transformed to a neuro-fuzzy network and then is trained by experimental recorded data of the system. The training procedure involves both gradient error back propagation (to adjust membership function coefficients) and LSE (to adjust linear output parameters).

These modeling methods can be applied to both static and dynamic systems. If the output of the model at a moment is applied as its input at the next moment; the model is called "dynamic model" or "recurrent model". In other words, in recurrent models, the output of the model at the existing moment, is influenced by the output of the model, at previous moments. For example, in a de-superheater, current outlet temperature of the de-superheater model is dependent on its outlet temperature in earlier moments. The nonlinear dynamic model can be described by the following non-linear discrete time equation:

$$\begin{cases} y(k) = f(Y^{k,l}; u^{k,m}) & \forall k \in \mathbb{N} \\ y(0) = y_0 \end{cases} \tag{1}$$

where for any vector such as X,

$$X^{k,l} := [X(k), X(k-1), \ldots, X(k-l)]$$

Dynamic systems can be modeled satisfactorily by recurrent neural or neuro-fuzzy networks, not by static (memory-less) networks.

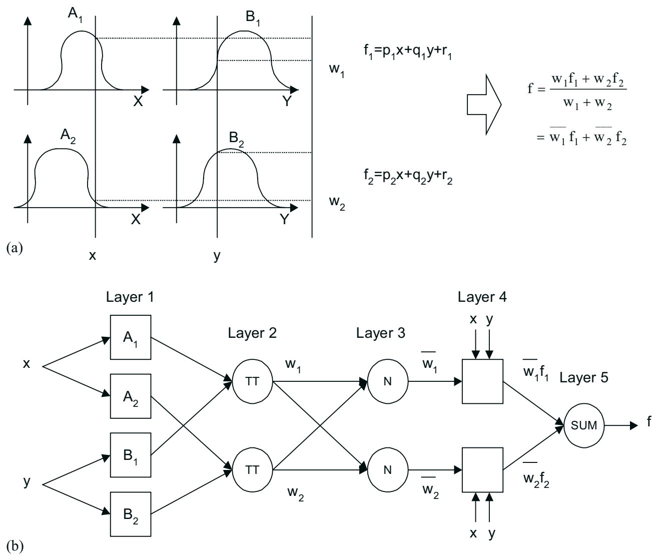

Figure 1: (a) A Sugeno-type fuzzy inference system; (b) a Sugeno-type neuro-fuzzy network.

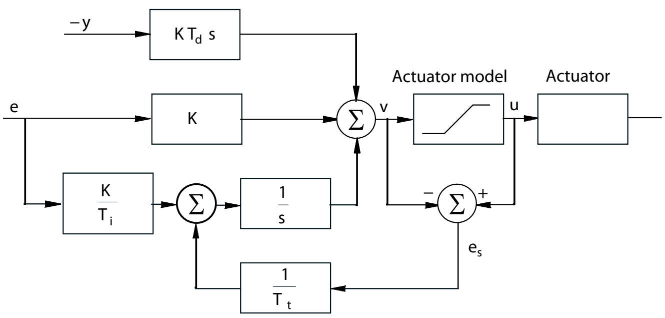

Figure 2: Controller with anti-windup where actuator output is not available.

2.2 PID Controller

Regardless of vast advances in the field of control systems engineering, PID scheme still remains the most common control algorithm in industrial use today. It is widely used because of its flexibility, high reliability and ease of operation and tuning (see for example [12]). A standard form of the PID controller is given in Eq. 2.

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau)d\tau + K_d \frac{de(t)}{dt} \tag{2}$$

The control $u(t)$ is a summation of three functions of the error $e(t)$, from a specified reference (demand or set-point) output $y_{sp}(t)$. Requirements on a control system may include many factors, such as response to command signals, insensitivity to measurement noise and process variations, and rejection of load disturbances. Proportional control has the effect of increasing the loop gain to make the system less sensitive to load disturbances, the integral of error is used principally to eliminate steady state errors, and the derivative action helps to improve closed loop stability. The parameters K_p, K_i, K_d are thus chosen to meet prescribed performance criteria, classically specified in terms of rise and settling times, overshoot and steady-state error, following a step change in the demand signal.

In many practical applications, due to the presence of noisy signals, the derivative action is frequently not used and many industrial controllers only have PI action. Another reason is that the derivative term increases sensitivity of the systems subjected to noise or disturbances, where it generates large outputs in presence of noisy or disturbed error signals [12].

In the standard form of PID control, the error enters linearly in the control algorithm, as it is shown in Eq. 2. It is sometimes desirable to have higher controller gains when the control error is large, and smaller gains when the control error is small. This can be accomplished by using the square of the control error. Thus, the control error is replaced by:

$$e_{squared} = e|e| \tag{3}$$

One reason for using error-squared signal is to reduce the effects of low-frequency disturbances in the measurement signal. These disturbances can not be filtered out, but the use of error-squared control gives a small amplification of the disturbance when the control error is small, and an effective control when the control error is large [12].

While many aspects of a control system can be understood based on linear control theory, some non-linear effects must be considered. In a control system with a wide range of operating conditions, it is a common fact that the actuator reaches its limit. This has severe consequences for control. Integral action in a PID controller is an unstable mode. This does not cause any difficulties when the loop is closed. The feedback loop will, however, be broken when the actuator saturates because the output of the saturating element is then not influenced by its input. The unstable mode in the controller may then drift to very large values. This means that the integral term "winds-up". Integrator windup can be avoided, by making sure that the integral is kept to a proper value when the actuator saturates, so that the controller is ready to resume action, as soon as the control error changes. This anti-windup scheme is known as tracking or back-calculation. A well-known form of tracking is linear feedback anti-windup, which is shown in the Figure 2 [12]. The actuator is represented by a signal limiter. The difference between actuator input and output $e_s(t)$, is fed back to the integrator through the gain $\frac{1}{T_t}$. As soon as the limiter saturates, this signal becomes non-zero and prevents the integrator from winding up. The tracking time constant T_t can be used to tune the value of anti-windup.

PID controller design methods differ with respect to the knowledge of the process dynamics they require. A standard method of setting the parameters is through the use of Ziegler-Nichols' tuning rules [13]. These techniques were developed empirically through the simulation of a large number of process systems to provide a simple rule. Optimization is a powerful tool for controller design, as well. The method is simple in conception. A control scheme with few parameters is specified. Next, system specifications are expressed as inequalities of functions of parameters. Then, the important specifications are chosen as a function (performance index) to be optimized. The method can be applied to design PID parameters easily. Different performance criteria for PID controllers are addressed in [12]. Indeed extra care must be exercised when defining performance index, since it may have many local minima. Another difficulty is the required computations may easily be excessive. However, new optimization techniques can conquer these difficulties.

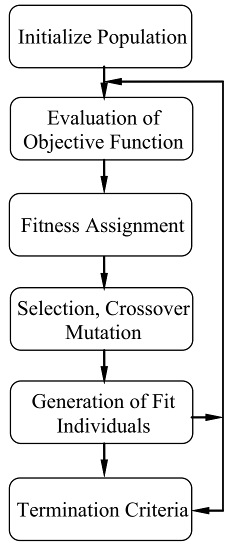

Figure 3: GA computational flow chart [14].

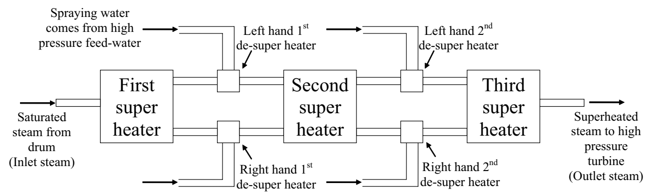

Figure 4: Super heating system of the steam power plant.

2.3 Genetic Algorithms (GAs)

In recent years there have been extensive researches on heuristic stochastic search techniques for optimization of proportional-integral-derivative gains [14]-[16]. A GA is a search/optimization technique that uses genetics and natural selection as a model for problem solving. In the GA, a population of randomly created individuals goes through a simulated process of evolution, which is a digital survival of the fittest in which individuals in the current population breed to produce new individuals hopefully better suited to the environment. Each individual represents a potential solution to the problem, a candidate set of parameter values. A GA works on the coding of the parameters and not on the exact parameters so that it does not depend on the continuity of the parameters or the existence of derivatives of the functions required in some conventional optimization algorithms. The coding method allows the GA to handle multi-modal (i.e., many-peaked) and multi-parameter type optimization problems easily, which are rather difficult or impossible to be treated with classical optimization methods. Salhi in [17] gives a general overview of heuristic search methods including GAs. The sequential steps for searching optimal solution using GA are shown in Figure 3. The GA is allowed to run iteratively until it reaches a predetermined ending condition. Different termination criteria may be used, such as limiting the maximum number of

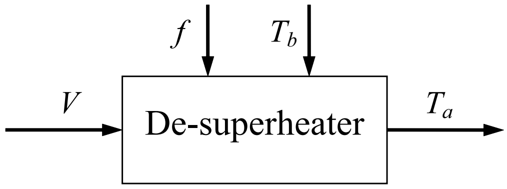

Figure 5: Inputs and the output of de-superheater.

generations, iterating until the best individual meets a targeted fitness, convergence based on fitness, maximum number of stall generations (sequence of consecutive generations), or when the least fit individual is fitter than the given criteria [18]. In this work assigning the maximum number of stall generations was used to terminate the search.

3 DESIGN OF GA-BASED PI CONTROLLER

3.1 Steam Power Plant De-superheater Dynamics

In this study a part of superheating system of a 4X 325 MW steam power plant is studied. The structure of a superheating system in a steam power generating plant is shown in Figure 4. For normal operation of the power plant and when the capacity of the power plant is over 30% of its nominal value, the desired output temperature of super-heater is 540 degrees Celsius. This temperature is adjusted at the de-superheater by spraying water through spraying valves. Figure 5 shows the inputs and the output of the second left-hand de-superheater where the three inputs are: inlet steam temperature T_b, mass flow rate of the spraying water V, and the steam mass flow rate f. The output is the steam temperature after spraying water T_a (outlet steam temperature). The steam mass rate (f) is summation of two other signals. The first signal is half of the total mass of the water flowing into the drum (after drum the steam flow is divided into two branches) and the second signal is the first de-superheater spraying water mass flow rate which is added to the main steam flow. The de-superheater dynamics is influenced by both of these signals with long time delays.

3.2 Neuro-Fuzzy Identifier Training

In this paper 1st order (linear) Sugeno type fuzzy inference systems are employed to model the process [7]. Figure 6 illustrates the input/output signals of the neuro-fuzzy model for the de-superheater in the discrete domain. In neuro-fuzzy model values of T_b, V, and f with respective time delays are introduced. Also, the values of T_a subjected to two time delays is included as inputs. The output of the neuro-fuzzy model is the outlet steam temperature of the de-superheater $T_a(k+1)$. The relation between the ten inputs and one output of Figure 6

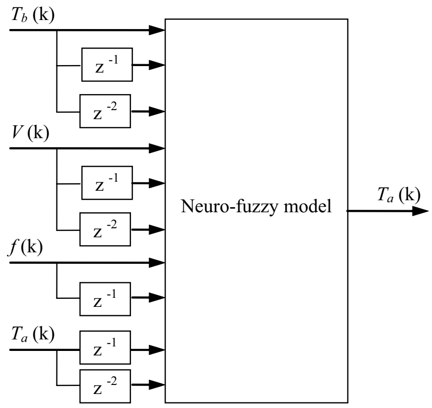

Figure 6: Inputs and output of the de-superheater's neuro-fuzzy model.

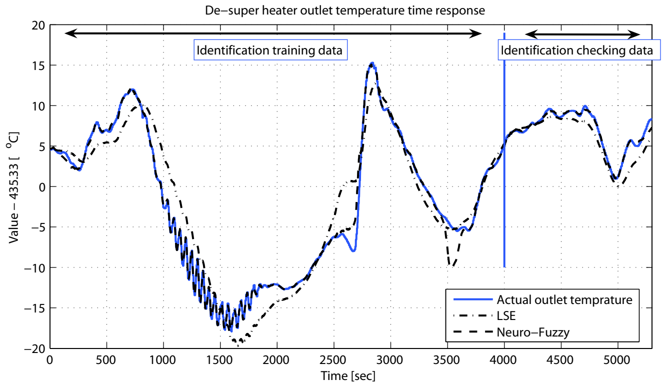

Figure 7: Training and testing data set for system identification.

for each fuzzy rule is given by the following equation:

$$\begin{cases} T_a(k+1) = \bar{\alpha} \times \left[T_b^{k,2}, V^{k,2}, f^{k,1}, T_a(k-1), T_a(k-2)\right]^T \\ \qquad\qquad +\alpha_{11} \qquad \forall k \in \mathbb{N} \\ T_a(0) = T_{a0} \end{cases} \tag{4}$$

where

$$\bar{\alpha} := [\alpha_1, \alpha_2, \ldots, \alpha_{10}]$$

In this equation all input variables have Gaussian membership functions. Parameters α_i and coefficients of Gaussian membership functions for all associated fuzzy rules are adjusted in the neuro-fuzzy model. Note that Eq. 4 is written for each fuzzy rule, while for simplicity the subscript of the associated fuzzy rule is omitted. Figure 7 shows the training and testing sets used to create the neuro-fuzzy and LSE models of the system. As it can be observed, in the neuro-fuzzy model approach the error is smaller than the LSE model. More details on the training the neuro-fuzzy model appear elsewhere [19], [20].

3.3 Outlet-Temperature-PI-Controller Development Based on Genetic Algorithms (GAPI)

As mentioned earlier, the outlet temperature of the de-superheater is subjected to powerful disturbances, which are inlet steam temperature (T_b) and steam mass flow rate (f). Another difficulty is that the set-point is constantly changing with time, thus a controller with good tracking ability is required. Current PID action controller operating on the system is designed to have very low sensitivity to disturbances and has very poor tracking ability. The most important problem in de-superheater control, however, is that the control signal reaches frequently to its minimum, where no cooling spray water $V = 0$. Considering these points, it is desired to modify current PID controller to have a better tracking ability as well as robustness to disturbances. To accomplish this goal, a new controller is designed for the region where disturbances are more powerful and set-point is changing fast in time. This guarantees the robustness of the controller in addition to its tracking ability. The desired region corresponds to $t = 1800 \sim 3000$ sec in Figure 7. New PI gains are tuned by GA (GAPI) to minimize a performance criteria through this region. In the GAPI formulation, the developed neuro-fuzzy model of the system acts as the plant and is the basis for evaluating the performance of the controller. The derivative action was not included because the de-superheater system in known to be noisy.

In order to find the best possible solution for the control problem, different controller structures are studied. It is clear that classical dynamic and steady-state measures of performance, e.g., over shoot, rise time, and settling time is inconveniencing in multi-step reference trajectory evaluation. This is particularly true when the final scalar objective function is to be a weighted sum of the different performance measures. Problem here arises in attaching weighting coefficients to each of these measures so that they correspond directly to the relative importance of the objectives or allow trade-offs between the objectives to be expressed. Hence, in this work integral criteria were considered as the measure of performance for the control system. Measures like integral of absolute error (IAE), the integral of time weighted square error (ITSE) and the integral of square time error (ISTE) are regularly used for PID tuning [12], [18]. In this study we employed a performance criterion (index), which is a combination of ISTE criteria and the integral of absolute values of the controller's command $|u|$ in order to minimize energy consumption, as shown in Eq. 5:

$$J = 1e-8 \int_0^{1200} \left(t^2|e(t)|^2 + 0.1|u(t)|\right) \tag{5}$$

Table 1
GA parameters

Population	25
Initial range	[0,1]
Selection	Stochastic uniform
Generations	25

This performance is minimized using a GA in order to tune parameters of different control structures. Parameters of the GA algorithm are given in Table 1. In this study several control strategies were investigated. First, PI action controller ($K_d = 0$ in Eq. 2) was used:

$$u_1(t) = K_p e(t) + K_i \int_0^t e(\tau)d\tau \tag{6}$$

Next, PI action controller with an anti-windup strategy was employed:

$$u_2(t) = K_p e(t) + \int_0^t \left(K_i e(\tau) + \frac{e_s(\tau)}{T_t}\right) d\tau \tag{7}$$

where $e_s(t)$ is the saturation error.

A PI action mechanism with squared error was also studied:

$$u_3(t) = K_{pe} e_{squared}(t) + K_i \int_0^t e(\tau)d\tau \tag{8}$$

where $e_{squared}$ is given in Eq. 3. As the fourth approach, PI action mechanism with squared error was combined with the anti-windup policy, where the control signal was generated in the following fashion:

$$u_4(t) = K_{pe} e_{squared}(t) + \int_0^t \left(K_i e(\tau) + \frac{e_s(\tau)}{T_t}\right) d\tau \tag{9}$$

The fifth, and the last control strategy is given in Eq. 10:

$$u_5(t) = K_{pe} e_{squared}(t) + \int_0^t \left(K_{ie} e_{squared}(\tau) + \frac{e_s(\tau)}{T_t}\right) d\tau \tag{10}$$

It should be noted that, in order to obtain valid results in all simulations, the control signal is subjected to theoretical actuator saturations, where the maximum absolute value for the rate of change of the control signal is set equal to 2 and the minimum control signal is selected to be zero. This model is used in the place of the unknown actual actuator operating in the de-superheater (see Figure 2). Parameters, of the mentioned control strategies were tuned by a GA in order to minimize the performance criteria given in Eq. 5. Controller parameters obtained by the declared syntheses are given in Table 2.

Results shown in Table 2 indicate that the fifth control strategy has the best performance. Thus, it is predictable that it would have least error and best robustness. There is another conclusion can be made from the Table 2. It can be seen that adding anti-windup scheme considerably improves the system's response. In the next section obtained results are discussed in details.

Table 2
Parameters of different control strategies obtained by optimizing modified ISTE performance criteria

Control Strategy	Description	No. of generations	J	K_p	K_i	K_{pe}	K_{ie}	$\frac{1}{T_t}$
u_1	PI action	59	59.3	2.292	0.0123	—	—	—
u_2	PI action with anti-windup	68	46.40	0.748	0.08	—	—	0.112
u_3	P action for square error and I action for error	42	66.42	—	0.02	0.886	—	—
u_4	P action for square error and I action for error with anti-wind up	95	49.26	—	0.12	0.412	—	1.15
u_5	PI action for square error with anti-windup	82	44.04	—	—	0.215	0.0323	0.321

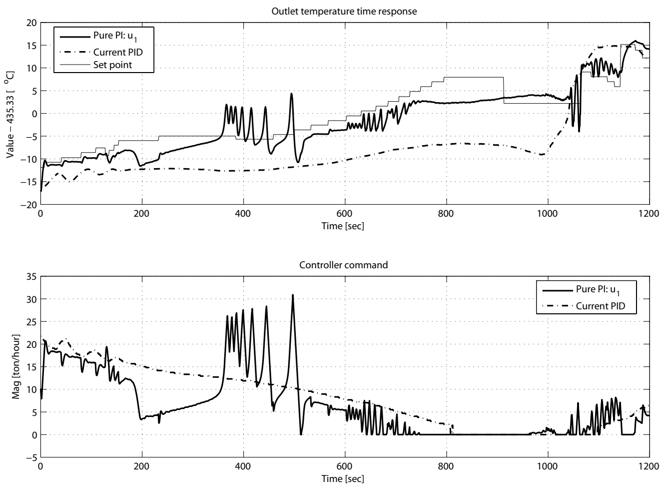

Figure 8: Dynamic time response of the de-superheater with pure PI controller.

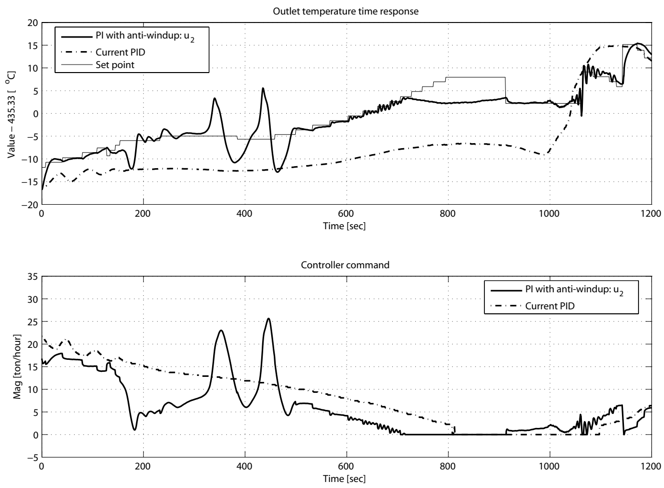

Figure 9: Dynamic time response of the de-superheater PI with anti-windup controller.

3.4 Outlet-Temperature-PI-Controller Performance Evaluation

In this section, the efficiency and the robustness of the designed control strategy for the de-superheater is studied and the performance of different schemes is compared. Since a standard PID type controller is the operating controller in the de-superheater control circuit of the studied power plant, it is employed for judgment in this paper. Simulations are performed using MATLAB/SIMULINK. First, the performance of the two PI action controllers, u_1 and u_2 are studied. The time response of the pure PI action and PI action with anti-windup are illustrated in Figures 8 and 9 respectively. It can be observed that the designed PI controller, although has smaller error tracking error than the current PID controller, its time response is very oscillatory and has very low damping. It is clear from the time response of the PI controller that the actuator saturates several times, thus, the "PI with anti-windup controller" must have much better performance. As expected, the "PI with anti-windup controller" shows much fewer oscillations while tracking the reference signal. This is clearly due to the anti-windup gain in the control loop. The system's dynamic performance is examined considering optimized "PI action for square error with anti-windup" as the controller. It is observed in Figure 10 that the controller follows the set point much better, while it damps out the oscillations rapidly.

To demonstrate the robustness of the designed GAPI controller (u_5), dynamic system's response for an interval out of the design region is depicted in Figure 11. As it is shown, although the disturbances are much different from disturbances in the design region, the controller is able to maintain the stability of the system and tracks the reference signal very closely, which clearly reveals that the proposed GAPI is quite robust to a wide range of variations in disturbances and set-point changes.

4 CONCLUSIONS

This paper demonstrates an application of artificial intelligent techniques in modeling and control of thermal power plant de-superheater. In this study, an effective controller for the second left hand de-superheater of a steam power plant with the capacity of 4X 325 MW is developed based on a previously identified plant using ANFIS technique. To develop the control strategy, different PI structures are optimized using genetic algorithms in order to boost the performance of the operating control circuit in the steam power plant. A GA is employed for automated controller tuning for assumed different PI controllers and optimizing the performance of the con-

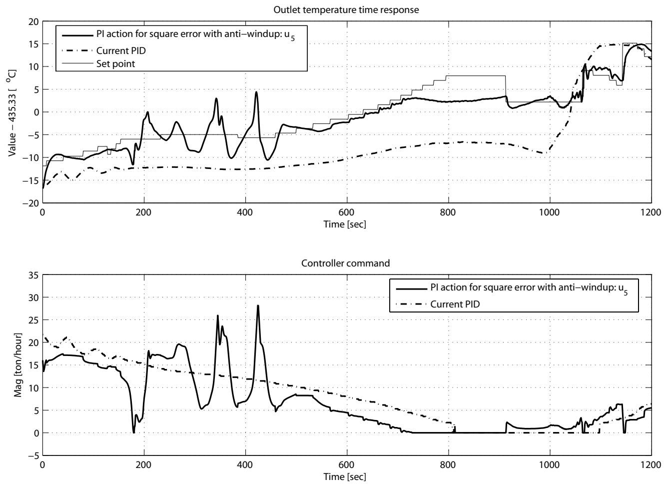

Figure 10: Dynamic time response of the de-superheater PI action for square error with anti-windup controller.

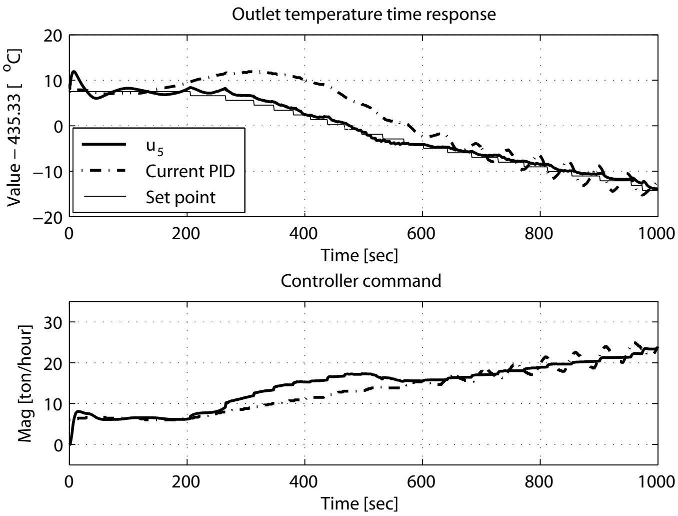

Figure 11: Dynamic time response of the de-superheater PI action for square error with anti-windup controller out of the design region.

trol strategy for the high-order non-linear thermal power plant subsystem. Results are reported to show practicability of the developed control law as well as its advantages over the operating controller.

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References

[1] A. Sanchez-Lopez, G. Arroyo-Figueroa, A. Villavicencio-Ramirez, "Advanced control algorithms for steam temperature regulation of thermal power plants," *Electrical Power and Energy Systems*, vol. 26, pp. 779-785, 2004.

[2] S. H. Lee, J. Kong, J. H. Seo, "Observers for bilinear systems with unknown inputs and application to superheater temperature control," *Control Engineering Practice*, vol. 5, no. 4, pp. 493-506, 1997.

[3] G. Arroyo-Figueroa, L. E. Sucar, A. Villavicencio, "Fuzzy intelligent system for the operation of fossil power plants," *Engineering Applications of Artificial Intelligence*, vol. 13, no.4, pp.431-439, 2000.

[4] J. R. Jang, "ANFIS: adaptive-network-based fuzzy inference systems," *IEEE Trans. on Systems, Man, and Cybernetics*, vol. 23, no. 3, pp. 665-685, 1993.

[5] C. E. Garcia, D. M. Prett, M. Morari, "Model predictive control; Theory and practice-A survey," *Automatica*, vol. 25, no. 3, pp. 333-348, 1989.

[6] S. J. Qin, T. A. Badgwell, "An overview of industrial model predictive control technology," *AIChE Symposium Series*, 1997.

[7] J. R. Jang, C. Sun, E. Mizutani, *Neuro-Fuzzy and Soft Computing*, Prentice-Hall, NJ, 1997.

[8] L. Ljung, *System Identification - Theory for the User*, 2nd edition, Prentice Hall, NJ, 1999.

[9] J. Vieira, F. Morgado Dias, A. Mota, "Artificial Neural Networks and Neuro-fuzzy Systems for Modeling and Controlling Real Systems: A Comparative Study," *Engineering Applications of Artificial Intelligence*, vol. 17, pp. 265-273, 2004.

[10] A. Afzalian, D. A. Linkens, "Training of neuro-fuzzy power system stabilisers using genetic algorithms," *International Journal of Electrical Power and Energy Systems*, vol. 22, no.2, pp. 93-102, 2000.

[11] H. Ghezelayagh, K. Y. Lee, "Training Neuro-Fuzzy Boiler Identifier with Genetic Algorithm and Error-Back Propagation," *IEEE Power Engineering Society Summer Meeting*, vol. 2, pp. 978 - 982, 1999.

[12] K. J. Astrom, T. Hagglund, *PID Controllers: Theory, Design, and Tuning*, ISA, Research Triangle Park, NC, 1995.

[13] J. G. Ziegler, N. B. Nichols, "Optimum setting for Automatic Controllers," *Trans. ASME*, vol. 64, pp. 759-768, 1942.

[14] M. Dubey, P. Gupta, "Design of Genetic-Algorithm Based Robust Power System Stabilizer," *International Journal of Computational Intelligence*, vol. 2, no. 1, pp. 48-52, 2005.

[15] C. Vlachos, D. Williams, J. B. Gomm, "Solution to the Shell standard control problem using genetically tuned PID controllers," *Control Engineering Practice*, vol. 10, no. 2, pp. 151-163, 2002.

[16] P. Wang, D. P. Kwok, "Optimal design of PID process controllers based on genetic algorithms," *Control Engineering Practice*, vol. 2, no. 4, pp. 641-648, 1994.

[17] S. Salhi, *Heuristic search methods*. In G. A. Marcoulides (Ed.), Modern methods for business research (chapter 6, p. 147), 1998. Lawrence Erlbaum Associates.

[18] M. M. Mwembeshia, C. A. Kenta, S. Salhi, "A genetic algorithm based approach to intelligent modelling and control of pH in reactors," *Computers and Chemical Engineering*, vol. 28, pp. 1743-1757, 2004.

[19] M. Mohammad-Zaheri, "Identification of thermal power plant subsystems using neuro-fuzzy algorithms," Masters of Science thesis, Department of Mechanical Engineering, University of Tehran, 2004 (in Persian).

[20] A. R. Mehrabian, A. Yousefi Koma, M. Mohammad-Zaheri, A. Ghaffari, D. Mehrabi, "Neuro-Fuzzy Modeling of Superheating System of a Steam Power Plant," in the Proceedings of the *24th IASTED International Multi-Conference on Artificial Intelligence and Applications* (AIA 2006), Innsbruck, Austria, Feb. 13-16, 2006, pp. 347-352.

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